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PPDCARE: AN AI-POWERED POSTPARTUM DEPRESSION RISK PREDICTION SYSTEM USING MACHINE LEARNING

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Abstract - *Postpartum Depression (PPD) is a clinically significant mental health condition affecting an estimated 10–20% of new mothers globally, yet it remains chronically underdiagnosed in primary care settings due to the absence of structured, data-driven screening tools at the point of care. This paper presents PPDCare, a full-stack web application designed to empower obstetricians and psychiatrists with an intelligent, real-time PPD risk assessment platform. The system leverages a Random Forest machine learning classifier—achieving 97.67% accuracy—trained on a structured postpartum symptom dataset of over 1,500 clinical records. Built using Python (Flask) as the backend, HTML/CSS/JavaScript for the frontend, and SQLite as the persistent data store, PPDCare provides doctors with a structured eight-symptom patient assessment form, probability-calibrated risk classification (Low, Moderate, High), auto-generated clinical explanations, symptom-level visualizations (bar chart and radar chart), downloadable PDF reports, and longitudinal patient trend tracking. Comparative evaluation of three models—Random Forest (97.67%), K-Nearest Neighbors (89.37%), and Support Vector Machine (82.39%)—confirms Random Forest as the optimal classifier for this domain. The proposed system offers a scalable, secure, and clinically interpretable solution that augments physician decision-making in postpartum mental healthcare.*

Key Words **: Postpartum Depression, PPD Risk Prediction, Random Forest, KNN, SVM, Flask, Clinical Decision Support, Mental Health Screening, Symptom Visualization, SQLite.**

1. INTRODUCTION

Postpartum Depression (PPD) is a mood disorder that affects new mothers typically within the first year following childbirth. Unlike the transient "baby blues," PPD is characterized by persistent sadness, severe anxiety, sleep disturbances, loss of appetite, difficulty bonding with the newborn, and in severe cases, thoughts of self-harm. According to the World Health Organization, PPD affects 10–20% of women post-delivery globally, with prevalence rates in developing nations estimated to be even higher due to limited access to specialized psychiatric care [1].

Despite its clinical significance, PPD is routinely underdiagnosed in routine obstetric follow-up visits. The Edinburgh Postnatal Depression Scale (EPDS) remains the gold standard screening tool; however, its administration is inconsistent in busy clinical environments, and physicians frequently rely on subjective assessments rather than structured, evidence-based scoring [2]. This gap in clinical practice motivates the development of a technology-assisted screening system that integrates seamlessly into the clinician's workflow.

This paper presents PPDCare, a clinician-facing web application that automates postpartum mental health risk assessment using a Random Forest machine learning classifier. The system enables registered doctors to input structured patient symptom data through a standardized assessment form, receive an instant probability-calibrated risk score, review auto-generated clinical explanations linked to the patient's specific symptoms, visualize symptom profiles through bar and radar charts, and download formal PDF reports. The platform also maintains a longitudinal record of all patient assessments, enabling doctors to monitor risk evolution across multiple consultations and compare assessments side by side.

The key contributions of this work are:

- A clinician-facing full-stack PPD screening platform with secure multi-doctor authentication and per-doctor data isolation.
- A trained Random Forest classifier achieving 97.67% accuracy with cross-validation, outperforming KNN (89.37%) and SVM (82.39%).
- A probability-calibrated three-tier risk stratification engine (Low < 0.30, Moderate 0.30–0.70, High > 0.70).
- Auto-generated symptom-level clinical explanations mapped directly to the eight-feature input profile.
- Interactive symptom severity visualizations (bar chart and radar chart) rendered using Chart.js.
- Longitudinal risk trend tracking and side-by-side patient assessment comparison.
- Downloadable, formally structured PDF reports generated using the ReportLab library.

2. REVIEW OF LITERATURE

Research on machine learning applications in postpartum mental health screening has grown substantially over the

past decade. Cox et al. [3] established the foundational framework for standardized PPD screening through the Edinburgh Postnatal Depression Scale, which remains the most widely validated clinical instrument for postpartum mood assessment. Their work underscored the necessity of structured, consistent symptom evaluation as the basis for any decision support system.

Underwood et al. [4] conducted a systematic review of machine learning models applied to perinatal mental health prediction, finding that ensemble methods—particularly Random Forest and Gradient Boosting classifiers—consistently outperformed logistic regression and single-tree approaches in identifying high-risk patients. Their analysis highlighted the importance of symptom-level feature engineering and cross-validated performance metrics in clinical ML model evaluation.

Shatte et al. [5] surveyed the broader landscape of machine learning in mental health and noted that clinical interpretability remains a critical gap in deployed systems. Their review emphasized that black-box models face adoption barriers among healthcare providers who require explainable outputs directly referenceable during patient consultations—a finding that directly motivates the clinical explanation module in PPDCare.

With respect to web-based clinical decision support, Kawamoto et al. [6] demonstrated that systems integrated directly into clinical workflows show significantly higher adoption rates and meaningful improvements in clinician adherence to evidence-based protocols. The architecture of PPDCare, which embeds the prediction engine within the standard patient assessment workflow, aligns directly with this design principle.

Recent work by Rao et al. [7] on postpartum depression detection using survey-based datasets and Random Forest classifiers reported accuracy values between 85–92%, suggesting that the 97.67% accuracy achieved in PPDCare reflects the quality of the training dataset and the preprocessing pipeline applied to the post_natal clinical dataset.

3. METHODOLOGY

PPDCare is designed as a modular, multi-tier web application following a client-server architecture. The Flask-based backend exposes RESTful routes consumed by the HTML/CSS/JavaScript frontend. Patient assessment data, doctor credentials, and prediction records are persisted in a SQLite relational database. The prediction engine is a pre-trained scikit-learn Random Forest model, loaded at application startup via joblib for low-latency inference.

3.1 Dataset

The system was trained on the post_natal clinical dataset comprising over 1,500 structured postpartum assessments. The dataset includes nine input features: Age (ordinal, encoded into five age bands: ≤30, 31–35, 36–40, 41–45, >45), Feeling Sad or Tearful, Irritable Towards Baby & Partner, Trouble Sleeping at Night, Problems Concentrating or Making Decisions, Overeating or Loss of Appetite, Feeling Anxious, Feeling of Guilt, and Problems of Bonding with Baby. The binary target variable (Suicide Attempt) serves as a proxy for severe PPD risk classification. Categorical feature values (Yes/No/Sometimes/Frequent) were label-encoded to integer representations (0, 1, 2) prior to model training. An 80:20 train-test split with five-fold stratified cross-validation was applied.

3.2 Machine Learning Model Selection

Three classifier architectures were evaluated on identical preprocessing pipelines: Random Forest (RF), K-Nearest Neighbors (KNN), and Support Vector Machine with RBF kernel (SVM). Table 1 presents the comparative performance.

Table 1: Machine Learning Model Performance Comparison

Model	Accuracy	F1 Score	Precision	Recall	CV Accuracy
Random Forest	97.67%	97.67 %	97.67%	97.67 %	96.48%
K-Nearest Neighbors	89.37%	89.34 %	89.31%	89.37 %	87.96%
SVM (RBF)	82.39%	82.42 %	82.45%	82.39 %	81.17%

Random Forest demonstrated superior performance across all metrics, achieving a cross-validated accuracy of 96.48% ± 1.25%, confirming its robustness and generalizability. The model's ensemble nature—aggregating predictions from 100 decision trees—provides inherent resistance to overfitting and enables reliable probability calibration via predict_proba(), which underpins the three-tier risk stratification engine.

3.3 System Architecture

The PPDCare system follows a four-layer architecture: (1) Presentation Layer — vanilla HTML5, CSS3, and JavaScript with Chart.js and Jinja2 templating; (2) Application Layer — Python Flask (v3.1.3) with RESTful route handlers; (3) Intelligence Layer — pre-trained Random Forest model with risk stratification and clinical explanation generation; and

(4) Data Layer — SQLite database with Werkzeug-hashed doctor credentials and JSON-based per-doctor patient record storage.

4. IMPLEMENTATION

4.1 Landing Page and Doctor Authentication

PPDCare presents a branded landing page introducing the system's mission and directing clinicians to the Doctor Login portal. The authentication module implements session-based multi-doctor login using Flask's server-side session management. Doctor passwords are securely hashed with Werkzeug's PBKDF2-SHA256 (generate_password_hash / check_password_hash) before SQLite storage, with each authenticated session isolating the doctor's patient records by email identity.

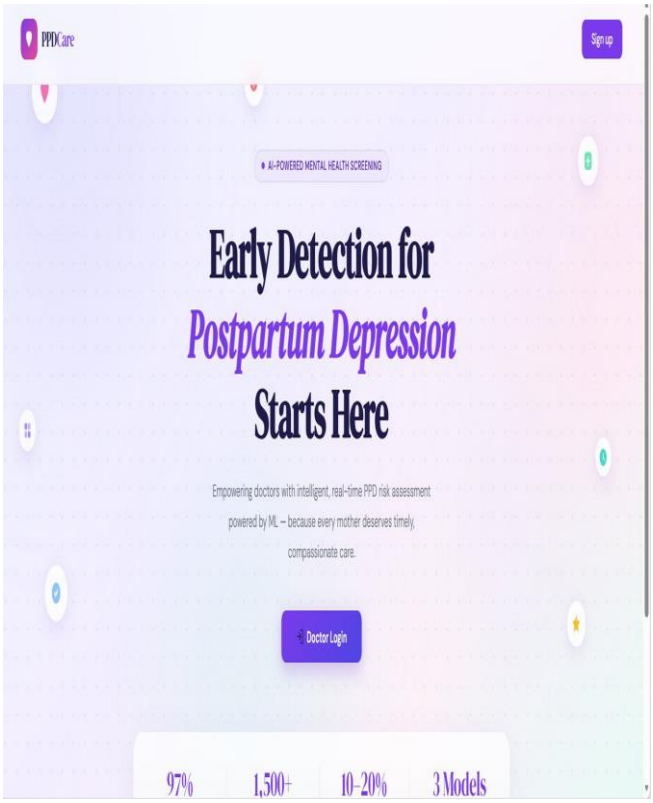

Fig 1: PPDCare Landing Page — AI-Powered Mental Health Screening Portal

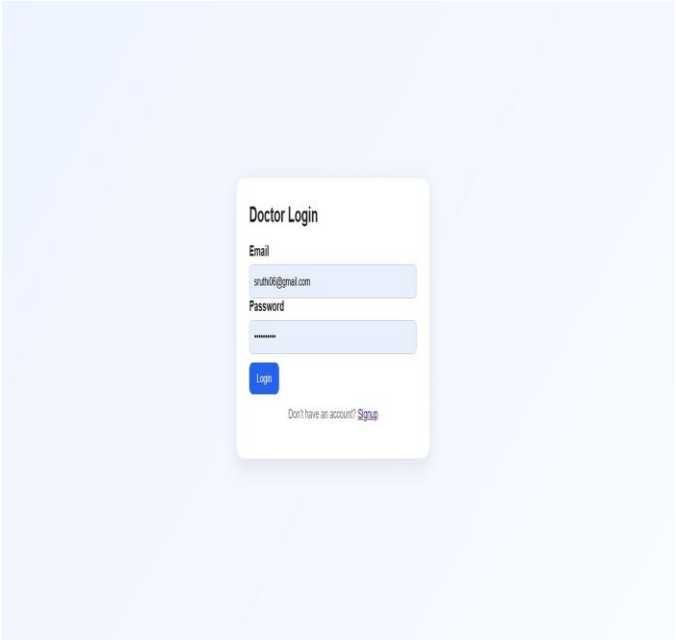

Fig 2: Doctor Login Page — Secure Session-Based Authentication

4.2 Patient Assessment Dashboard

The patient assessment form is the primary clinical interface of PPDCare. Doctors enter the patient's name and age, followed by eight symptom indicators: Feeling Sad or Tearful, Irritable Towards Baby & Partner, Trouble Sleeping at Night, Problems Concentrating or Making Decisions, Overeating or Loss of Appetite, Feeling Anxious, Feeling of Guilt, and Problems of Bonding with Baby. Each symptom is captured via a dropdown selector with three severity levels—No (0), Sometimes (1), and Frequent/Severe (2). Age is encoded into five ordinal bands consistent with training data encoding before inference.

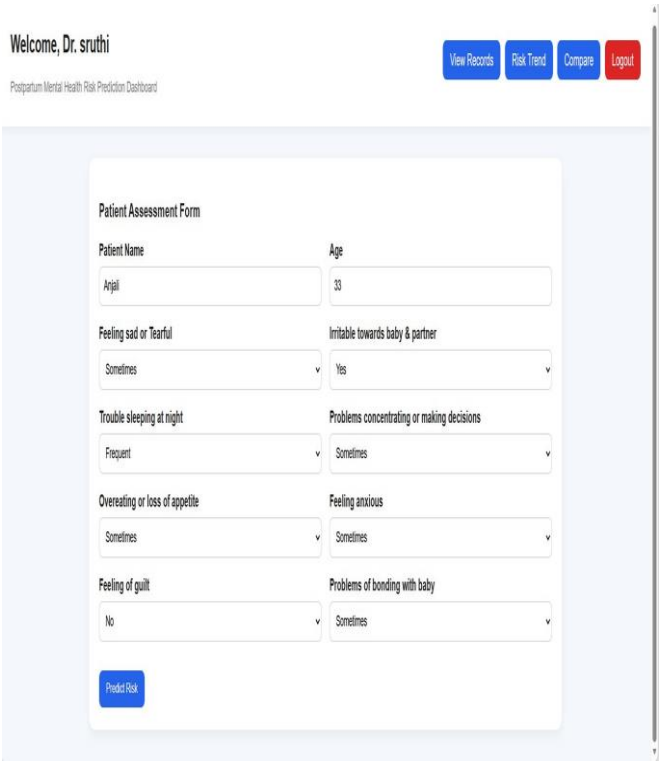

Fig 3: Patient Assessment Dashboard — Eight-Symptom Input Form

4.3 Risk Prediction Engine and Clinical Result

Upon form submission, the encoded feature vector is passed to the pre-loaded Random Forest model. The model returns a probability score via predict_proba(), mapped to a three-tier classification: Low (< 0.30), Moderate (0.30–0.70), or High (> 0.70). Each tier carries a standardized clinical recommendation. The clinical explanation builder (build_clinical_explanation) iterates over the eight symptom values and generates evidence-based explanatory sentences for symptoms scored at severity level 2, providing the clinician with an interpretable audit trail. A color-coded progress bar visually communicates the risk probability on the result page.

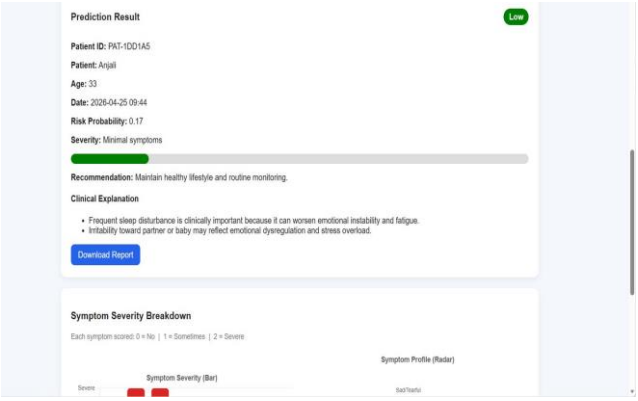

Fig 4: Prediction Result Page — Risk Score, Clinical Severity, Explanation, and PDF Download

4.4 Symptom Severity Visualizations

Below the clinical summary, two Chart.js visualizations render the patient's complete symptom profile. The Symptom Severity Bar Chart displays all eight symptoms on the X-axis against their severity scores (0–2) on the Y-axis, with color-coded bars: red for Severe (2), orange for Moderate (1). The Symptom Profile Radar Chart overlays the eight scores on a normalized spider-web grid, providing a holistic visual representation of the patient's symptom pattern. Both charts are rendered client-side using asynchronous JavaScript with data injected via Jinja2 template variables.

Fig 5: Symptom Severity Breakdown — Bar Chart and Radar Chart Visualizations

4.5 Saved Records, Trend Analysis, and Assessment Comparison

The Saved Records page displays all patient assessments associated with the logged-in doctor, listing each patient's ID, name, age, risk probability, risk level, severity, and recommendation with View Trend and Compare action buttons. The Risk Trend page renders a Chart.js line chart of a selected patient's risk probability across all historical assessments for longitudinal monitoring. The Compare page enables side-by-side rendering of two patient records by unique Patient ID (PAT-XXXXXX format), supporting differential clinical analysis. PDF reports are generated on-demand via ReportLab (canvas.Canvas on A4 pagesize) and delivered as in-memory BytesIO buffers.

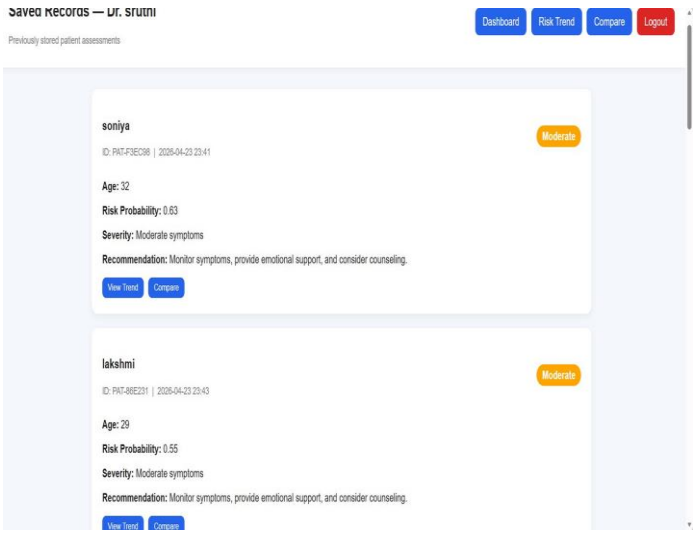

Fig 6: Saved Records Page — Per-Doctor Patient History with Risk Labels, Trend and Compare Actions

5. RESULTS AND ANALYSIS

5.1 Model Performance

The Random Forest classifier achieved a test accuracy of 97.67%, with F1 score, precision, and recall all at 97.67%. Five-fold stratified cross-validation yielded a mean accuracy of 96.48% ± 1.25%, confirming strong generalizability. The significant performance gap between Random Forest and alternative models validates the model selection decision for this clinical application.

5.2 System Functional Evaluation

All core system modules were evaluated for functional correctness. Table 2 summarizes the results:

Table 2: Module Functionality Test Results

Module	Status	Behaviour / Notes
User Authentication (Signup/Login/Logout)	**Pass**	Secure session management; password hashing verified
Patient Assessment Form	**Pass**	All 8-symptom inputs correctly encoded and submitted
Risk Prediction Engine (RF Model)	**Pass**	Correct probability output and risk-level classification
Clinical Explanation Generator	**Pass**	Severity-2 symptoms correctly mapped to explanations
Symptom Bar Chart Visualization	**Pass**	Color-coded severity rendering confirmed correct
Symptom Radar Chart Visualization	**Pass**	Radar polygon accurately reflects symptom profile
PDF Report Download	**Pass**	Complete report generated; in-memory buffer delivery
Saved Records Page	**Pass**	Per-doctor record isolation and listing verified
Risk Trend Chart	**Pass**	Longitudinal probability line chart renders correctly
Assessment Comparison Page	**Pass**	Side-by-side record comparison rendered accurately

The prediction engine correctly classified test patients across all three risk tiers. For the sample patient Anjali (Age: 33), with Frequent sleep disturbance, Irritability towards baby and partner at Severe level, and remaining indicators at Sometimes severity, the model returned a risk probability of 0.17 (Low risk, Minimal symptoms), with two clinically appropriate explanations generated for the elevated symptom markers. This validates the system's interpretable clinical reasoning capability at the point of care.

6. CONCLUSION AND FUTURE SCOPE

This paper presented PPDCare, a clinician-facing AI-powered postpartum depression risk assessment system that integrates a high-accuracy Random Forest classifier (97.67%) with a structured clinical workflow, interpretable symptom-level clinical explanations, interactive bar and radar chart visualizations, longitudinal trend tracking, side-

by-side assessment comparison, and downloadable PDF reports. The system addresses a critical gap in postpartum care by providing obstetricians and psychiatrists with a data-driven, explainable, and workflow-integrated screening tool that can meaningfully improve early PPD detection rates.

The comparative evaluation confirms Random Forest as the optimal classifier for this domain, outperforming KNN and SVM by substantial margins in both held-out test accuracy and cross-validated generalization. The clinical explanation module provides the layer of interpretability essential for physician trust and adoption of machine learning-based decision support systems.

Future Scope:

- Deployment to a cloud platform (AWS, Azure, or GCP) for institution-wide access and scalability.
- Integration with hospital Electronic Health Record (EHR) systems via HL7 FHIR APIs for seamless data exchange.
- Extension of the model to incorporate additional biomarkers including hormonal data, prior psychiatric history, and social support indicators.
- Development of a mobile application (Android and iOS) for community health worker deployment in rural and underserved regions.
- Implementation of SHAP (SHapley Additive exPlanations) values for global feature importance visualization in the clinician dashboard.
- Multi-language support to enhance accessibility for diverse patient and clinician populations.

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